Air Qual Atmos Health
DOI 10.1007/s11869-010-0086-3

Does attainment status for the PM_{10} National Air Ambient Quality Standard change the trend in ambient levels of particulate matter?

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Received: 4 February 2010 / Accepted: 12 August 2010

Abstract Despite increasingly stringent and cost-demanding national, state, and local air quality regulations, adverse health effects associated with ambient exposure to air pollution persist. Accountability research, aimed at evaluating the effects of air quality regulation on health outcome, is increasingly viewed as an essential component of responsible government intervention. In this paper, we focused on assessing the impact of air quality regulations on ambient levels of air pollution. We considered two groups of counties: the first group (A) includes counties that in 1991 were designated as in attainment or unclassifiable with respect to the 1987 National Ambient Air Quality Standards (NAAQS) and maintained their status through 2006; the second group ($\overline{\mathrm{A}}$), includes counties that in 1991 were designated as nonattainment and were subsequently redesignated as in attainment. We hypothesized that if air pollution control programs adopted to meet the NAAQS are effective in reducing air pollution levels, counties in group $\overline{\mathrm{A}}$ will experience a sharper decrease in PM_{10} levels than counties in group A. To provide evidence to support this hypothesis, Bayesian hierarchical models were developed for estimating 1) the yearly percentage change in ambient PM_{10} levels for 100 counties and the entire USA during the period 1987–2007 and 2) the change in PM_{10} ambient levels in counties in group $\overline{\mathrm{A}}$ compared with counties in group A. We found statistically significant evidence of variability across counties in trends of PM_{10} concentrations. We also found strong evidence that counties transitioning from nonattainment to attainment status during the period 1987–2007 experienced a sharper decline in PM_{10} when compared with counties that were always in attainment.

Keywords Particulate matter · Bayesian methods · Hierarchical models · National Ambient Air Quality Standards · Accountability · Environmental epidemiology

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Introduction

Over the last few decades, many efforts have been taken to improve air quality because of the known effects of exposure to air pollutants on health. In the USA, ambient PM_{10} (particulate matter with aerodynamic diameter less than or equal to 10 μm) concentrations have declined by approximately 30% during the period 1990–2006 (US Environmental Protection Agency 2008b). Despite increasingly stringent and cost-demanding national, state, and local air quality regulations, adverse health effects associated with ambient exposure to air pollution persist (Dominici et al. 2006; Peng et al. 2008; Pope et al. 2009). Accountability research (Health Effects Institute 2003), aimed at evaluating the effects of air quality regulation on health

Published online: 26 August 2010

outcome, is increasingly viewed as an essential component of responsible government intervention.

In 2003, the Health Effects Institute Accountability Working Group proposed a conceptual framework for research on accountability that considers the air quality management process from regulatory action to potential changes in emissions, ambient levels of pollutants and ultimately adverse health effects (Health Effects Institute 2003). One of the largest national regulatory intervention programs in the USA results from the requirements of the Clean Air Act (CAA). The CAA requires the US Environment Protection Agency (EPA) to set National Ambient Air Quality Standards (NAAQS) for six principal pollutants, known as "criteria pollutants". Primary standards are intended to protect public health, while secondary standards protect public welfare such as visibility or crops. When a new NAAQS for a specific pollutant is adopted or an existing standard is revised, each county (or portion of county) in the USA is designated as: (1) attainment, if the area meets the NAAQS for that specific pollutant; (2) nonattainment if the area does not meet the NAAQS; (3) unclassifiable if the area cannot be classified on the basis of available information as meeting or not meeting the NAAQS. Areas classified as nonattainment are required to implement control strategies established through state implementations plans (SIPs) to reduce pollutant emissions in order to meet the standards. If the NAAQS are met after the initial nonattainment designation, the areas can be re-designated as in attainment. The CAA generally requires that an area designated as nonattainment achieve attainment status no later than 5 years from the nonattainment designation date, although EPA may extend this date for another five years with a possible 2-year further extension (US Environmental Protection Agency 2006c). States that contain areas redesignated as in attainment are required to implement maintenance plans, explaining how the State will provide for maintenance of such standard for at least 20 years (US Environmental Protection Agency 2006b).

In this paper, we hypothesized that if the air pollution control programs adopted to meet the NAAQS are effective in reducing air pollution levels, then counties transitioning from nonattainment to attainment status will experience a sharper decline in PM_{10} levels when compared with counties that were always in attainment.

More specifically, we considered two group of counties: Group A includes counties that in 1991 were designated as in attainment or unclassifiable with respect to the 1987 NAAQS and that maintained their status during the 1991–2006 period, which included revisions of the PM_{10} NAAQS in 1997 and 2006. Group $\overline{A}$ includes counties that in 1991 were designated as nonattainment with respect to the 1987 NAAQS and that were subsequently redesignated as in attainment prior to 2007. To provide evidence that supports this hypothesis, Bayesian hierarchical models were developed for estimating (1) the yearly percentage change in ambient PM_{10} levels for 100 counties and the entire USA during the period 1987–2007 and (2) the additional decrease in the PM_{10} ambient levels in counties in group $\overline{A}$ compared with counties in group A. We considered that changes in PM_{10} levels might be influenced by temporal changes in the economy. For example a decrease in PM_{10} levels could be a consequence of a decline in industrial and mobile source emissions related to a decline in the US economy and not a direct effect of air pollution regulations (Chay and Greenstone 2003). For this reason, we adjusted our estimates by county specific measures of socio-economic status (SES).

Materials and methods

Data

We assembled monthly time series of PM_{10} levels for 100 US counties for the period 1987–2007. The PM_{10} data were obtained from the US EPA AirData database (US Environmental Protection Agency 2008a). The database includes the 24-h average daily PM_{10} concentrations for 2,944 monitoring stations in the USA for the period 1987–2007. For each county, we first calculated the daily average PM_{10} concentration by averaging levels across monitors with at least 75% of the data available and with no data gaps longer than 1 month. To account for the effects of outliers, if a county had more than one monitoring station, we took a 10% trimmed mean of the measurements from all available stations.

We then assembled a dataset which denotes the attainment status with the 1987 NAAQS for PM_{10} for each county. The attainment status for each county is determined based on a comparison of the most recent three consecutive years of monitoring data with the level and form of the NAAQS. More specifically, a county is classified as in attainment if the annual average of PM_{10} concentrations is equal to or below 50 μg/m^3 (EPA revoked the annual PM_{10} NAAQS in December 2006) and the daily average of PM_{10} concentrations is equal to or below 150 μg/m^3 not to be exceeded more than once a year on average over three years. A county is classified as nonattainment if air pollution levels exceed the NAAQS. In addition if a county has emission sources that contribute to a violation of the NAAQS in another county, that county might also be designated as nonattainment area. If a county is not attaining the NAAQS for a particular pollutant, its State is required to submit a SIP, indicating all the strategies that will be adopted in order to achieve compliance with the NAAQS. Based on air quality data and a state request for redesignation, the EPA is required to determine whether an area has subsequently attained the NAAQS. The determination is based on the NAAQS as of the designated attainment date. A county is designated as unclassifiable for a particular criteria pollutant if the available information are insufficient to determine whether that area meets the NAAQS (US Environmental Protection Agency 2006a). Unclassifiable areas, in fact, do not have monitoring data or may have only old monitoring data that is not considered representative for the statutory period considered for the attainment status designation process. Typically these are low density, relatively rural population areas that are not linked to a nonattainment area and therefore are not required to have monitors in place. Unclassifiable areas are generally subject to the same regulatory requirements as attainment areas, and for this reason we considered these two groups of counties together. The attainment/nonattainment status classification with respect to the 1987 PM_{10} NAAQS used for this analysis was obtained from the EPA November 6, 1991 Federal Register notice (US Environmental Protection Agency 1992). County name, PM_{10} annual average concentrations, and attainment status as of 1991 and 2007 can be found in Table 1. We also assembled county specific annual estimates of per-capita personal income for each year from 1987 to 2007. Per capita personal income is defined as the total income from all sources received by all the residents of a specific county divided by the resident population of that area. SES indicators were obtained from the Bureau of Economic Analysis (U.S. Department of Commerce. Bureau of Economic Analysis 2009). Annual data were utilized and applied to the monthly PM data analyses. For our analysis we defined two groups of counties: the first group, denoted as group A, includes (a) all the counties that in 1991 were designated as in attainment with respect to the 1987 NAAQS and that remain in attainment through 2006 ($N = 6$) and (b) all the counties that were designated as unclassifiable and that did not change their status ($N = 62$) through 2006. The second group, denoted as group $\overline{\mathrm{A}}$, includes all the counties that in 1991 were subsequently designated as nonattainment with respect to the 1987 NAAQS ($N = 14$) and that were redesignated as in attainment prior to 2007. Fig. 1 shows the locations of 100 US counties included in the study.

Methods

In this section, we introduce Bayesian hierarchical models for: (1) estimating the yearly percentage change in ambient PM_{10} levels for each of the 100 US counties and on average across all the counties; (2) quantifying the evidence supporting the hypothesis that counties in group $\overline{\mathrm{A}}$ experienced a faster decline in PM_{10} ambient levels than counties in group A. To estimate county-specific and national average linear trends of PM_{10} concentrations, we used the following two-stage Bayesian hierarchical model. At the first stage, we assumed:

$$\log(x_t^c) = \beta_0^c + \beta_1^c(t - \overline{t}) + \varepsilon_t^c,\ c = 1 \ldots C\ t = 1 \ldots T \quad (1)$$

where x_t^c is the log average PM_{10} concentrations at month t in county c, β_0^c is the logarithm of the county-specific $\log(PM_{10})$ concentration at month $t = \overline{t}$ and β_1^c is the county-specific monthly rate of change in PM_{10}. At the second stage, we assumed:

$$\boldsymbol{\beta}^c | \boldsymbol{\beta} \sim N_2(\boldsymbol{\beta}^c, \boldsymbol{\Sigma})$$

independent for each county = 1,..., 100 where $\boldsymbol{\beta} = (\beta_0, \beta_1)$ denotes the overall regression coefficients on average across all counties and $\boldsymbol{\Sigma}$ is 2×2 covariance matrix where the diagonal elements denote the variance of β^c from the national mean β and the off-diagonal elements denote the covariance between β^c and $\beta^{c'}$. At the third stage we specified the following prior distributions: the prior distribution for $\boldsymbol{\beta}$ was multivariate normal with large variances and prior distribution for $\boldsymbol{\Sigma}$ was an inverse Wishart.

We fitted the model using Markov chain Monte Carlo (MCMC) methods implemented by the software package JAGS (Plummer 2009). We obtained an estimate of the posterior distribution of all parameters of interest $(\boldsymbol{\beta}^c, \boldsymbol{\beta}, \Sigma)$. More specifically, we estimated the posterior distribution of the annual percentage change in PM_{10} ambient levels defined as $\delta^c = 100 \times 12 \times \beta_1^{c(j)}$, where $\beta_1^{c(j)}$ is the j-posterior sample for the marginal posterior distribution $p(\beta_1^c|\text{data})$. In order to check if our regression model had residual autocorrelation, we plotted the autocorrelation function of the residuals. For all the counties, the plot of the residual autocorrelation function was near 0 after one lag, indicating that our model was adequate.

To estimate the association between change in attainment status and long-term trend changes in PM_{10} levels, we introduced a second Bayesian hierarchical model. Because temporal changes in the economy might influence changes in PM_{10} levels, we included

Table 1 County-specific attainment status with respect to 1987 NAAQS and PM_{10} concentration for the years 1987 and 2007

FIPS	County	State	Region	Attainment status (1991)	Attainment status (2006)	PM_{10} conc 1987 ($\mu g/m^3$) (*)	PM_{10} conc 2007 ($\mu g/m^3$) (**)
17031	Cook	IL	IM	Nonatt	Att	38.04	27.98
18097	Marion	IN	IM	Att	Uncl	37.17	27.32
29510	St. Louis	MO	IM	Uncl	Uncl	26.50	24.76
39035	Cuyahoga	OH	IM	Nonatt	Att	39.64	29.86
42003	Allegheny	PA	IM	Nonatt	Att	49.21	28.11
55079	Milwaukee	WI	IM	Uncl	Uncl	27.43	25.18
1113	Russell	AL	NA	Uncl	Uncl	26.14	22.79
4007	Gila	AZ	NA	Att	Nonatt	55.42	33.63
6007	Butte	CA	NA	Uncl	Uncl	32.44	21.37
6017	El Dorado	CA	NA	Uncl	Uncl	24.40	14.32
6027	Inyo	CA	NA	Nonatt	Nonatt	23.81	18.19
6031	Kings	CA	NA	Nonatt	Nonatt	98.42	44.80
6045	Mendocino	CA	NA	Uncl	Uncl	29.48	11.98
6061	Placer	CA	NA	Uncl	Uncl	23.63	17.50
6079	San Luis Obispo	CA	NA	Uncl	Uncl	23.59	14.20
6081	San Mateo	CA	NA	Uncl	Uncl	34.91	19.03
6083	Santa Barbara	CA	NA	Uncl	Uncl	22.21	19.58
6089	Shasta	CA	NA	Uncl	Uncl	31.67	14.96
6111	Ventura	CA	NA	Uncl	Uncl	36.25	28.87
8099	Prowers	CO	NA	Nonatt	Att	29.32	25.72
8107	Routt	CO	NA	Att	Nonatt	29.17	23.89
9001	Fairfield	CT	NA	Uncl	Uncl	33.55	30.30
9003	Hartford	CT	NA	Uncl	Uncl	23.47	16.46
9005	Litchfield	CT	NA	Uncl	Uncl	22.15	4.00
9009	New Haven	CT	NA	Nonatt	Att	31.69	21.01
9011	New London	CT	NA	Uncl	Uncl	22.00	18.00
16005	Bannock	ID	NA	Nonatt	Uncl	53.06	23.08
17119	Madison	IL	NA	Nonatt	Att	24.00	31.76
17143	Peoria	IL	NA	Uncl	Uncl	23.20	25.80
17163	St. Clair	IL	NA	Uncl	Uncl	42.53	32.71
17197	Will	IL	NA	Uncl	Uncl	34.71	24.44
18019	Clark	IN	NA	Uncl	Uncl	50.74	18.89
18167	Vigo	IN	NA	Uncl	Uncl	29.53	22.57
21019	Boyd	KY	NA	Uncl	Uncl	37.93	21.70
21059	Daviess	KY	NA	Uncl	Uncl	34.08	21.71
21199	Pulaski	KY	NA	Uncl	Uncl	26.32	11.70
23003	Aroostook	ME	NA	Nonatt	Att	15.70	12.99
23017	Oxford	ME	NA	Uncl	Uncl	21.48	11.47
27137	St. Louis	MN	NA	Uncl	Uncl	26.05	24.69
30029	Flathead	MT	NA	Att	Nonatt	42.00	13.05
31025	Cass	NE	NA	Uncl	Uncl	44.33	25.10
35013	Dona Ana	NM	NA	Nonatt	Uncl	61.73	33.20
35017	Grant	NM	NA	Uncl	Uncl	40.28	20.83
32031	Washoe	NV	NA	Nonatt	Nonatt	43.49	31.72
36013	Chautauqua	NY	NA	Uncl	Uncl	18.16	7.38
36059	Nassau	NY	NA	Uncl	Uncl	20.28	13.30
39017	Butler	OH	NA	Uncl	Uncl	32.08	23.25
39085	Lake	OH	NA	Uncl	Uncl	27.60	18.94
39087	Lawrence	OH	NA	Uncl	Uncl	29.46	20.98
39099	Mahoning	OH	NA	Uncl	Uncl	31.05	21.41
39145	Scioto	OH	NA	Uncl	Uncl	40.42	20.60
39151	Stark	OH	NA	Uncl	Uncl	34.01	23.74
39155	Trumbull	OH	NA	Uncl	Uncl	24.50	19.80
41029	Jackson	OR	NA	Nonatt	Att	83.30	22.70
41035	Klamath	OR	NA	Nonatt	Att	137.67	22.62

Table 1 (continued)

FIPS	County	State	Region	Attainment status (1991)	Attainment status (2006)	PM_{10} conc 1987 ($\mu g/m^3$) (*)	PM_{10} conc 2007 ($\mu g/m^3$) (**)
41039	Lane	OR	NA	Nonatt	Uncl	34.74	14.54
41051	Multnomah	OR	NA	Nonatt	Att	46.65	17.04
41061	Union	OR	NA	Nonatt	Att	69.10	19.17
46103	Pennington	SD	NA	Uncl	Uncl	28.48	26.45
47065	Hamilton	TN	NA	Uncl	Uncl	43.57	22.08
48061	Cameron	TX	NA	Uncl	Uncl	23.09	17.08
49049	Utah	UT	NA	Nonatt	Uncl	33.04	24.92
51035	Carroll	VA	NA	Uncl	Uncl	27.72	18.16
51047	Culpeper	VA	NA	Uncl	Uncl	21.29	18.63
51630	Fredericksburg	VA	NA	Uncl	Uncl	21.90	19.23
51187	Warren	VA	NA	Uncl	Uncl	27.84	18.92
51840	Winchester	VA	NA	Uncl	Uncl	31.17	20.29
55133	Waukesha	WI	NA	Uncl	Uncl	34.17	25.78
54009	Brooke	WV	NA	Att	Nonatt	36.17	24.90
54029	Hancock	WV	NA	Nonatt	Att	49.79	23.69
54069	Ohio	WV	NA	Uncl	Uncl	28.10	21.68
56005	Campbell	WY	NA	Uncl	Uncl	12.46	13.04
56037	Sweetwater	WY	NA	Uncl	Uncl	18.47	18.68
36111	Ulster	NY	NE	Uncl	Uncl	16.33	6.13
6001	Alameda	CA	NW	Att	Uncl	31.77	19.06
8001	Adams	CO	NW	Nonatt	Att	46.99	38.19
8041	El Paso	CO	NW	Att	Uncl	27.13	21.35
53063	Spokane	WA	NW	Nonatt	Att	17.41	8.53
6019	Fresno	CA	SC	Nonatt	Nonatt	48.85	33.65
6037	Los Angeles	CA	SC	Nonatt	Nonatt	60.87	32.88
6065	Riverside	CA	SC	Nonatt	Nonatt	79.11	57.71
6071	San Bernardino	CA	SC	Nonatt	Nonatt	80.15	53.48
6073	San Diego	CA	SC	Att	Uncl	40.05	28.28
1073	Jefferson	AL	SE	Uncl	Uncl	38.87	27.67
1089	Madison	AL	SE	Uncl	Uncl	34.52	21.70
12031	Duval	FL	SE	Uncl	Uncl	31.70	25.87
12057	Hillsborough	FL	SE	Uncl	Uncl	28.74	24.69
12095	Orange	FL	SE	Uncl	Uncl	32.60	18.95
12103	Pinellas	FL	SE	Uncl	Uncl	29.50	20.34
13121	Fulton	GA	SE	Uncl	Uncl	36.43	24.06
47037	Davidson	TN	SE	Uncl	Uncl	40.32	25.54
47157	Shelby	TN	SE	Uncl	Uncl	32.96	26.41
48113	Dallas	TX	SE	Att	Uncl	37.17	26.87
48201	Harris	TX	SE	Att	Uncl	41.74	57.55
4013	Maricopa	AZ	SW	Nonatt	Nonatt	68.45	44.92
4019	Pima	AZ	SW	Nonatt	Uncl	39.27	28.97
48141	El Paso	TX	SW	Nonatt	Uncl	53.96	31.58
48303	Lubbock	TX	SW	Uncl	Uncl	33.72	20.13
20209	Wyandotte	KS	UM	Uncl	Uncl	41.05	29.79
31055	Douglas	NE	UM	Uncl	Uncl	34.15	33.38

*If the PM10 time series was not available for the year 1997, the first available time series of PM10 has been used
**If the PM10 time series was not available for the year 2007, the first available time series of PM10 has been used

as covariate in the model a county-specific measure of SES. At the first stage, we assumed:

$$\log(x_t^c) = \beta_0^c + \beta_1^c(t-\overline{t}) + \beta_2^c I^c + \beta_3^c(t-\overline{t})I^c + \\ +\beta_4^c(z_t^c - \overline{z}^c) + \varepsilon_t^c \qquad (2)$$

where I^c is equal to 1 if the county c belongs to group $\overline{\mathrm{A}}$ or $I^c = 0$ is the county c belongs to group A. The parameters β_0^c and $\beta_0^c + \beta_2^c$ denote the logarithm of the county-specific PM_{10} concentration at time $t = \overline{t}$ for counties in group A and $\overline{\mathrm{A}}$ respectively, when $z^c = \overline{z}_t^c$. z_t^c is the average per-capita personal income at time t, for each subject in county c. The parameters β_1^c and $\beta_1^c + \beta_3^c$ denote the county-specific monthly rate of change in PM_{10} for counties that belong to A and $\overline{\mathrm{A}}$ respectively, when $z^c = \overline{z}^c$ and β_4^c is the county-specific increment in $\log(PM_{10})$ concentration associated with a \$1,000 increase in per-capita personal income with respect to the average value. The income value was available only on yearly basis, so we used the same annual estimate for all the months in the same year. To reduce correlation between parameters, we centered the covariates.

At the second stage we assumed: $\boldsymbol{\beta}^c|\boldsymbol{\beta} \sim N_5(\boldsymbol{\beta}, \boldsymbol{\Psi})$, independent for each county $c = 1, \ldots, C$, where $C =$ 82 is the number of counties included in the analysis. The parameter $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_4)$ is the overall mean for the counties and $\boldsymbol{\Psi}$ is a covariance matrix of dimension a 5×5. The diagonal element Ψ_{cc} denotes the variance of each β^c from its overall mean β. The off-diagonal element $\Psi_{cc'}$ denotes the covariance between β^c and $\beta^{c'}$. With regard to the prior used in the model, $\boldsymbol{\beta}$ was multivariate normal with large variances and prior distribution for $\boldsymbol{\Psi}$ was an inverse Wishart.

The marginal posterior distributions of the parameters of interest $(\boldsymbol{\beta}^c, \boldsymbol{\beta}, \boldsymbol{\Psi})$ were estimated by MCMC methods, using the package JAGS. We estimated the posterior probability $p(\beta_3 < 0|\text{data})$, where the parameter β_3 represents the difference in the logarithm of PM_{10} trend between counties in groups A and $\overline{\mathrm{A}}$: if β_3 is less then zero that means that PM_{10} levels for counties is group $\overline{\mathrm{A}}$ are decreasing faster than for counties in group A. The posterior probability that β_3 is negative is a measure of the strength of the evidence that the designation as nonattainment status and subsequent redesignation as in attainment, following implementation of the SIP, determines a faster decline in PM_{10} concentrations than being always in attainment.

Sensitivity analysis

As a sensitivity analysis, we estimated the parameters of interest using alternative modeling and estimating approaches. Firstly, we fitted the following fixed effect model:

$$\log(x_t^c) = \beta_0 + \beta_1(t - \overline{t}) + \beta_2 I^c + \beta_3(t - \overline{t}) I^c + \\ + \beta_4(z_t - \overline{z}) + \varepsilon_t \tag{3}$$

and we estimate $\boldsymbol{\beta}$ using ordinary least square (OLS; model A); secondly, we obtained an OLS estimate of $\boldsymbol{\beta}$ with robust standard errors (model B), to account to the residual spatial autocorrelation between county-specific trend estimates.We fitted these models using R. Thirdly, we fitted a linear mixed-effects model with a county-specific slope and intercept, as in model 2 (model C) and we estimated $\boldsymbol{\beta}$ by maximizing the restricted maximum likelihood function.

We then estimated the parameter of models 2 and 3, excluding from the analyses all the unclassifiable counties in group A.

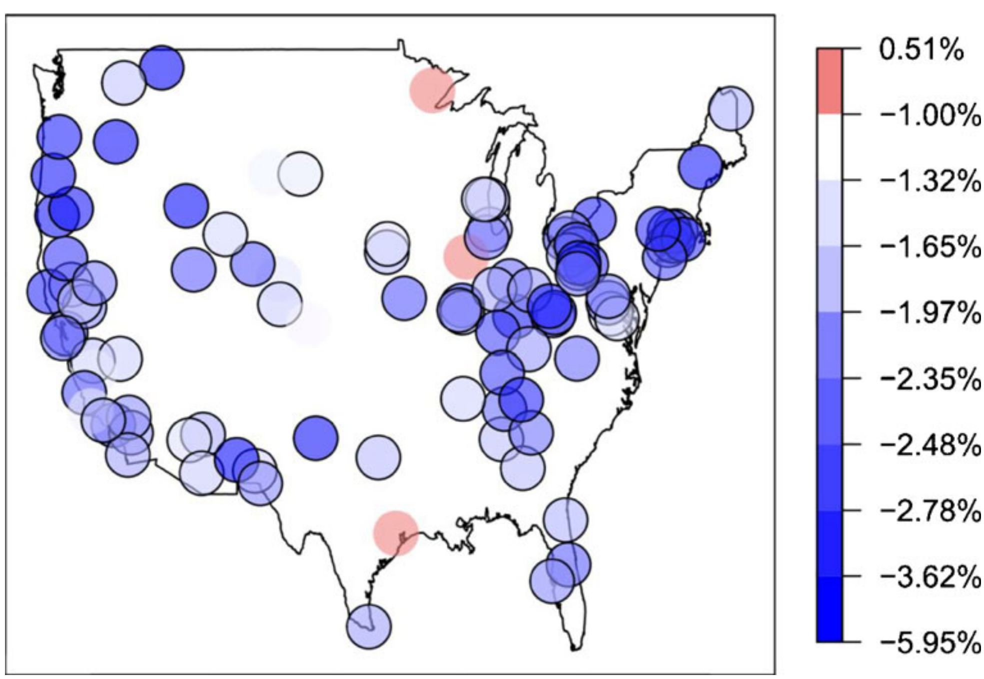

Fig. 1 Map of the US 100 counties. The color scale is proportional to the yearly percentage change in PM_{10} levels during the period 1987–2007. The *bold outline* denote that in that county the decline in PM_{10} is statistically significant different from zero

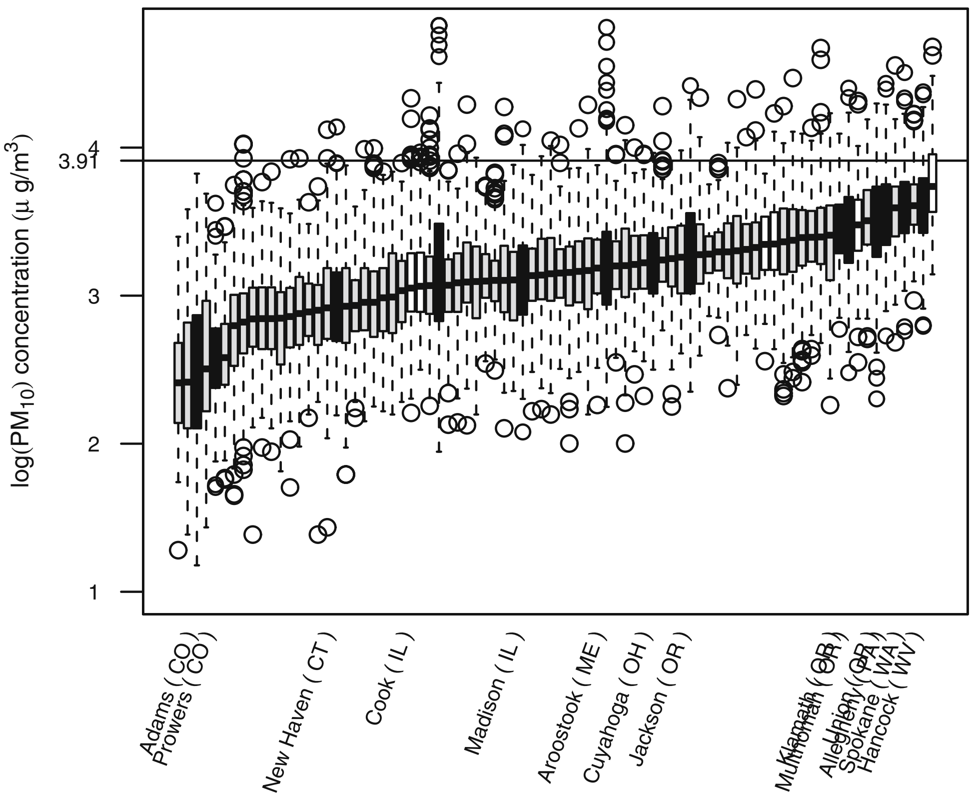

Fig. 2 Boxplots of county-specific log monthly PM_{10} concentrations for counties in group A initially in attainment with the NAAQS (*white*) or unclassifiable (*grey*) and $\overline{A}$ (*black*). Group A includes counties that in 1991 were designated as in attainment ($N = 6$) or unclassifiable ($N = 62$) with respect to the 1987 NAAQS and that maintained their status through 2006 . Group $\overline{A}$ includes counties that in 1991 were designated as nonattainment with respect to the 1987 NAAQS ($N = 14$) and that were redesignated as in attainment prior to 2007. The *horizontal line* corresponds to the logarithm of the PM_{10} National Air Quality Standard for 1987. Counties are ranked from the smallest to the largest median of PM_{10} values across the time period

Results

Figure 1 shows the map of 100 counties where the color scale of each circle is proportional to yearly percentage change in PM_{10} levels. The circles with the black outline indicate the yearly percentage changes statistically different from zero. We found that, on average across the 100 counties, the yearly PM_{10} concentrations decreased by −2.20% (95% posterior interval (PI) −2.45, −1.93). The sharpest declines were found in Bannock (ID) (−4.98, 95% PI −5.98, −3.92) and in flathead (MT) (−5.95, 95% PI −6.85, −5.07). PM_{10} levels decreased in 97 out of 100 counties and the decline was statistically significant for 97 counties out of 100.

Figure 2 shows boxplots of county-specific monthly PM_{10} concentrations for the 82 out of the 100 US counties included in this analysis. The black boxplots are for counties in group $\overline{A}$, while the white and grey boxplots are for counties in group A in attainments with the NAAQS or unclassifiable. The horizontal line corresponds to the 1987 NAAQS for annual PM_{10} concentration. The medians of the PM_{10} concentrations for

Table 2 Point estimates and 95% intervals of β_0 and β_1 denoting the average log(PM_{10}) concentration at time $t = \overline{t}$ and the annual PM_{10} trend for counties in group A, β_2 and β_3 denoting the difference in the average log(PM_{10}) concentration at time $t = \overline{t}$ and the annual PM_{10} decline for county in group $\overline{A}$

Var	Fixed effect model (OLS) (A)	Fixed effect model and robust std err (OLS) (B)	Random effect model (MLE) (C)	Bayesian random effect model (MCMC) (D)
	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% PI)
Group A				
β_0	3.432 (3.414, 3.45)	3.434 (3.411, 3.458)	3.517 (3.402, 3.633)	3.117 (2.95, 3.27)
β_1	−0.019 (−0.03, −0.027)	−0.019 (−0.021, −0.017)	−0.037 (−0.045, −0.028)	−0.034 (−0.043, −0.025)
Group $\overline{A}$				
$\beta_0 + \beta_2$	3.593 (3.554, 3.632)	3.593 (3.547, 3.639)	3.679 (3.443, 3.916)	5.077 (4.817, 5.298)
$\beta_1 + \beta_3$	−0.029 (−0.032, −0.026)	−0.029 (−0.033, −0.025)	−0.040 (−0.051, −0.028)	−0.083 (−0.11, −0.066)

Parameter estimates were obtained by fitting a fixed effect model (A), a fixed effect model with robust standard errors (B), a random effect model (C), a Bayesian random effect model (D), all adjusted by SES

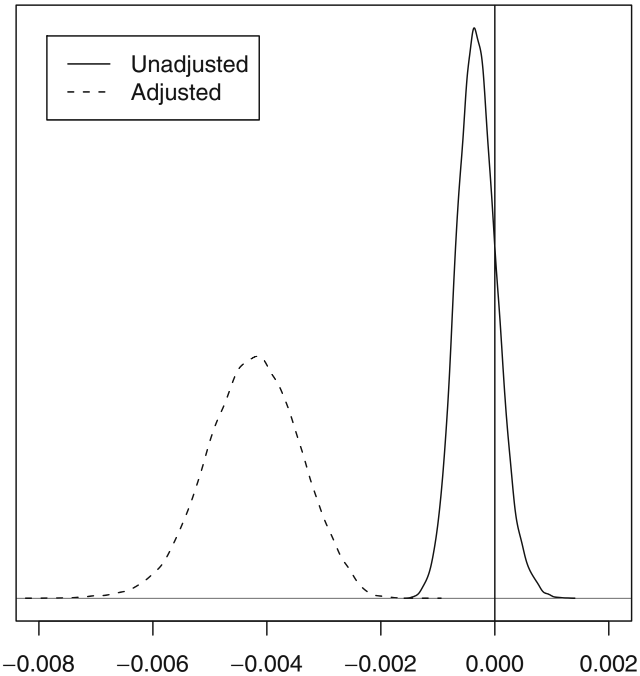

Fig. 3 Posterior distribution of β_3, where the parameter β_3 represents the difference in the logarithm of PM_{10} trend between counties in groups A and $\overline{\mathrm{A}}$: if β_3 is less then zero that means that PM_{10} levels for counties is group $\overline{\mathrm{A}}$ are decreasing faster than for counties in group A. The posterior probability that β_3 is negative is a measure of the strength of the evidence that the designation as nonattainment status and subsequent redesignation as in attainment, following implementing SIP, determines a faster decline in PM_{10} concentrations. Parameter estimates were obtained by fitting a Bayesian random effect model unadjusted (*straight*) and adjusted (*dotted*) by SES

all the counties in groups A and $\overline{\mathrm{A}}$ were equal to 24.8 and 26.5 μ/m^3, respectively.

Table 2 summarizes the results of model 2, when PM_{10} trend was estimated using fixed effect models (A–B) and hierarchical models (C–D). In all these models, the parameters β_1 and $\beta_1 + \beta_3$ represent the log(PM_{10}) trend for counties in groups A and $\overline{\mathrm{A}}$. Similarly, the parameters β_0 and $\beta_0 + \beta_2$ represent the log average PM_{10} concentration at time $t = \overline{t}$ for groups A and $\overline{\mathrm{A}}$, respectively. With the hierarchical model (C), we calculated the intraclass correlation coefficient (ICC): the ICC was equal to 0.70 indicating that the 70% of the total variance in the PM_{10} concentrations over time is due to differences between the counties considered. Using the Bayesian hierarchical model (D) we found that counties in group $\overline{\mathrm{A}}$ had a steeper decrease in PM_{10} concentrations than counties in group A. The percentage change in annual PM_{10} concentrations for counties in group $\overline{\mathrm{A}}$ was $\delta_{\overline{\mathrm{A}}} = -2.22$ (95% PI −3.08, −1.11) and for counties in A was $\delta_A = -2.08$ (95% PI −2.34, −1.82). Figure 3 shows the posterior distribution of the parameter β_3 estimated using a Bayesian hierarchical model nonadjusted and adjusted for SES. When we do not adjust per SES the posterior probability that β_3 is lower than 0 was 84%, but when we adjusted per income the posterior probability that β_3 is lower than 0 was 1%, indicating that counties in $\overline{\mathrm{A}}$ had a steeper decline in monthly PM_{10} levels than counties in A and the difference in PM_{10} trend between the two groups of counties was statistically significant. Results were robust to alternative specifications of the statistical models and were confirmed also when unclassifiable counties were excluded from the analyses (see Table 3): in particular the posterior probability $P(\beta_3 < 0)$ was equal to 1%.

Discussion

In this paper, we provided evidence that in 97 out of 100 counties in the USA ambient levels of PM_{10} decreased over time during the period 1987–2007. We found a statically significant evidence (p<0.001) of variability

Table 3 Point estimates and 95% intervals of β_0 and β_1 denoting the average log(PM_{10}) concentration at time $t = \overline{t}$ and the annual PM_{10} trend for counties in group A that were always in attainment ($n = 6$), β_2 and β_3 denoting the difference in the average log(PM_{10}) concentration at time $t = \overline{t}$ and the annual PM_{10} decline for county in group $\overline{\mathrm{A}}$($n = 14$)

Var	Fixed effect model (OLS) (A)	Fixed effect model and robust std err (OLS) (B)	Random effect model (MLE) (C)	Bayesian random effect model (MCMC) (D)
	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% PI)
β_0	3.69 (3.63, 3.75)	3.69 (3.65, 3.74)	3.58 (3.47, 3.69)	3.38 (2.8, 3.79)
β_1	−0.04 (−0.04, −0.03)	−0.04 (−0.04, −0.03)	−0.03 (−0.04, −0.03)	−0.02 (−0.04, 0.003)
Group $\overline{\mathrm{A}}$				
$\beta_0 + \beta_2$	3.78 (44.77, 45.9)	3.78 (44.78, 45.89)	3.65 (3.42, 3.87)	3.58 (37.34, 48.16)
$\beta_1 + \beta_3$	−0.05 (−0.05, −0.04)	−0.05 (−0.05, −0.04)	−0.04 (−0.05, −0.03)	−0.03 (−0.05, −0.005)

Parameter estimates were obtained by fitting a fixed effect model (A), a fixed effect model with robust standard errors (B), a random effect model (C), a Bayesian random effect model (D), all adjusted by SES across counties in the trends of PM_{10} concentrations. We also found that counties originally designated as nonattainment with respect to the 1987 PM_{10} NAAQS but that subsequently achieved attainment status (group $\overline{A}$) had a sharper decline in annual PM_{10} levels than counties that were originally designated as in attainment or unclassifiable with respect to the 1987 PM_{10} NAAQS and maintained their status through 2006 (group A).

Air pollution levels have declined over the past two decades in the USA. The EPA reports a decreasing trend for all the six criteria air pollutants: in particular, the decline in PM_{10} concentration was estimated to be 30% from 1990–2006, while the national emissions from various sources (fuel combustion, transportation, industrial process) of PM_{10} decreased of 31% during 1988–2003 (US Environmental Protection Agency 2008b). Our results showed an annual average decrease in PM_{10} of 2.2%, that is an overall decrease of 45% for the period 1987–2007.

A relatively small but growing body of studies has addressed the decline in ambient air pollutants levels as a consequence of environmental policies implementation. (Chay et al. 2003; Cirera et al. 2009; Ward et al. 2008; Goodman et al. 2009). Greenstone (2003) quantified the effect of regulatory policies on air pollution levels, estimating the average percentage change in industrial emissions over time of lead, particulate matter, and ozone as a function of the county attainment status with respect to the pollutant-specific NAAQS. Bachmann (2008) provided an overview of the EPA emissions and air quality forecasts for the six criteria pollutants, that can be seen as an useful tool for evaluating improvements air pollution air quality resulting from emissions reductions programs.

Other epidemiological studies assessed the impact of decline in air pollution levels on improvement of public health indicators (Hedley et al. 2002; Heinrich et al. 2002; Tonne et al. 2008). Peters et al. (2009) found an association between decline for all cause mortality and decreasing levels of ultrafine particles, CO and ozone as a consequence of strict environmental controls and modernization of industry, transportation and household heating in Erfurt. Another German study (Heinrich et al. 2002) showed that declines of total suspended particulates and sulfur dioxide in eastern Germany after reunification lead to a decrease in prevalence of nonallergic respiratory symptoms. Other papers proposed new methods for estimating the association between variations in ambient air pollution levels and variations in mortality rates over space and time (Janes et al. 2007). In particular, Shin et al. (2009) obtained city-specific estimates of health risk using a spatio-temporal random effects model in a Bayesian framework and proposed an indicator for estimating trend in health outcomes as a consequence of variations in air pollution concentrations. Similarly, we applied Bayesian hierarchical methods to obtain a statistical method for evaluating the impact of air pollution control measures on ambient air pollutants. Bayesian methods are, in fact, a suitable approach for specifying and fitting hierarchical regression models: this approach has been frequently employed in the analysis of longitudinal data and in time-series studies of air pollution and health (Dominici et al. 2000; Koop and Tole 2004).

Several epidemiological studies have found an association between a decline in air pollution and longer survival. In particular, Pope and colleagues estimated an increase in life expectancy of 0.61 years associated with a decrease of 10 $\mu g/m^3$ in fine particulate matter concentration (Pope et al. 2009). Other studies have provided evidence of an association between decline in PM_{10} and decline in mortality for all-cause mortality and cardiovascular mortality (Clancy et al. 2002; Laden et al. 2006).

Beside the implementation of air pollution controls included in the SIP, other factors could be responsible for the decline in PM_{10} trend. Changes in long-term particulate matter levels in ambient air can be affected by changes in multiple factors, such as population demographics, industrial activity, and energy demand.

In this analysis, we accounted for county-level population socio-economic status and did not assess the impact of any other potential confounders. The SES has been previously used as economic indicator that relates to air pollution levels (Chay and Greenstone 2003). Furthermore, there is also a direct elasticity relationship between vehicle miles traveled and household income, with a 10% increase in household income increasing daily VMT by 3.5–3.7% (Pickrell and Schimek 1997) which results in an increase in motor vehicle pollution emissions; therefore, a 10% decrease in household income would result in an equivalent decrease in VMT and a decrease related motor vehicle pollution.

Inclusion of time-varying area-level characteristics did not greatly change air pollution trend estimates, even though adjustment for SES highlighted a stronger and statistically significant difference in PM_{10} decline in counties in $\overline{A}$ with respect to counties initially in group A as shown in Fig. 3. Another limitation of our study is that we excluded from our analyses counties in attainment with the NAAQS at the beginning of the study that transited to the nonattainment status. We also did not take into account information on county-specific SIPs, for example, date of implementation and type of SIP for each study area, because such information were not known for each county. The control strategies included in the SIP and employed by nonattainment counties varied significantly by region, because were selected based on identification of the major sources contributing to an area's PM_{10} problem via development of an emissions inventory. For example, wood-burning in woodstoves and fireplaces, as well as disturbance of unpaved roads by vehicle travel, were often major sources of PM_{10} in the Pacific Northwest and the Rocky Mountain regions. Control strategies in these areas therefore included requirements for use of EPA-certified woodstoves, and in some areas prohibition on the installation of new woodstoves and/or fireplaces, as well as paving of roads. For areas in the Mid-West and Northeast regions, major industrial sources (e.g., industrial boilers, steel mills and coke ovens) were a major contributor to PM_{10} levels, and control strategies in these areas included requirements for installation of more advanced pollution control equipment.

In this paper, we only considered the designation as attainment or nonattainment counties at two time points: when each county was classified as in attainment or nonattainment with respect to the 1987 NAAQS during 1991 and 2007. Though EPA revised the form of the NAAQS for PM_{10} in 1997, subsequent litigation rescinded the revised PM_{10} standard and EPA reinstated the 1987 standard (American Trucking Ass'ns 2002). As a further analysis, the model used in the study could allow for random changing point corresponding to every change in the designation status. These analyses, also, could be repeated routinely for future revisions of the NAAQS. Assessment of the relationship between implementation of national and state-level air pollution control measures to changes in ambient air quality levels and ultimately to health outcomes can provide important information regarding the efficacy of air quality management policies. The statistical methods here proposed could be further applied to assess the impact of air pollution control measures on public health. However, given the relatively limited current body of science in this area, a substantial emphasis on supporting future efforts will be needed if the potential for the accountability paradigm to inform public policy is to be realized.

Acknowledgements The project described was supported by Award Number R01ES012054 from the National Institute of Environmental Health Sciences, Award Numbers EPA R83622 and EPA RD83241701. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute of Environmental Health Sciences, of the National Institutes of Health nor of the EPA.

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